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Comparison of a Cell-Based Energy Conservation Technique and MST Topology Control in Wireless Ad Hoc Networks

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Abstract

Cooperative strategies and topology control protocols have been recently proposed as effective techniques to reduce energy consumption in wireless ad hoc networks. Although these approaches share the same goal of extending network lifetime, they can be considered as orthogonal approaches. So far, the energy savings achieved by the two techniques have not been directly compared in a unified framework. Thus, it is not clear under what conditions does one of the techniques outperform the other. In this paper, we make a first step in answering this question. First, based on theoretical as well as experimental results presented in the literature, we identify the "best" cooperative and topology control mechanisms, and we define an idealized framework for comparison. Then, we compare their performances (in terms of network lifetime extension) in the previously defined framework by means of extensive simulations, both in stationary and mobile networks. This comparison yields several insights into the relative performances of cooperative and topology control techniques.

1 Introduction

Applications of wireless ad hoc networks are numerous and potential applications far greater [1]. The combination of battery-operated devices with power-intensive RF circuitry makes energy conservation in ad hoc networks an important topic. When considering an important sub-class of wireless ad hoc networks, namely sensor networks, energy conservation becomes even more important due to size, weight, and power restrictions and a limited ability to replace or recharge batteries in many sensor applications.

Cooperative strategies and topology control protocols have been recently proposed in the literature as major approaches to reducing energy consumption in ad hoc networks. Cooperative strategies are motivated by the fact that, for many wireless transceivers, there is little difference between the energy consumed by the interface during transmission, reception, and listening. These strategies therefore operate by having neighboring nodes coordinate times during which nodes can completely shut down their interfaces, potentially resulting in large energy savings if the coordination overhead is limited. Topology control protocols, on the other hand, take advantage of the at least squared reduction in transmit power that results from reducing the distance that a transmission must reach. In these protocols, nodes reduce their transmit power while still attempting to guarantee that each node can reach a sufficient number of neighbors for the network to remain connected.

Although both cooperative techniques and topology control protocols share the goal of conserving energy, they can be considered as orthogonal techniques. Both approaches operate at an intermediate layer, between the routing and the MAC layers, with the goal of achieving a considerable network lifetime extension *over the case where no energy-saving technique is used*[1]. It has been shown that adoption of energy-savings mechanisms at the routing (or MAC) layer only achieves quite limited lifetime extension.

While cooperative strategies and topology control protocols share the goal of reducing energy consumption, to date they have not been directly compared in a unified framework. Thus, it is not clear which technique is *more* effective under which conditions. In this paper, we make a first step towards answering this question. First, we identify, based on theoretical as well as experimental results presented in the literature, the "best" cooperative and topology control mechanisms, and define an idealized framework for comparison. Then, we compare their performances (in terms of network lifetime extension) in the previously defined framework by means of extensive simulations.

It is our opinion that the results presented here represent novel contributions towards a better understanding of

- the relative performance of the two techniques, and with respect to the no energy conservation approach, under different conditions (load, node density, node number, and mobility);

[1]For the sake of brevity, in the rest of this paper we will drop this specification and simply speak of "network lifetime extensions".

- the effect of the lifetime definition on the results;
- more realistic traffic models.

2 Related work and motivation

Measurements on off-the-shelf wireless transceivers have shown sleep:idle:receiving:transmitting ratios of 0.025:1:1.2:1.7 for a AT&T 2Mb/s WaveLAN card [37], and of 0.06:1:1.2:1.8 for a Lucent WaveLAN card operating at 11 Mb/s [12]. Cooperative strategies exploit this by shutting down the interface most of the time. Clearly, the nodes sleeping periods must be carefully scheduled, since otherwise the network functionality may be compromised. To do this, some classes of "equivalent" nodes are identified, and only one node in every class (called the *representative*, or *leader*, node) is left active. Periodically, the set of active nodes is changed to achieve a more uniform energy consumption and/or to deal with mobility.

Cooperative strategies differ in the definition of "equivalence" between nodes, in the way the classes of "equivalent" nodes are identified, and in the leader election algorithm used in every "class of equivalence". A widely used notion of node equivalence is *routing equivalence*: k nodes $\{u_1, \ldots, u_k\}$ are routing equivalent if they play identical roles with respect to routing (i.e., if no additional connectivity is achieved in the network by having more than one u_i active).

Several routing cooperative strategies have been recently proposed in the literature. In [37], Xu, et al., introduce the GAF strategy, which is based on a subdivision of the network deployment region into an appropriate number of non-overlapping cells. The cells are used to identify equivalent nodes: all the nodes lying in the same cell are proved to be routing equivalent. An election algorithm is periodically executed to elect the leader in every cell. In the SPAN algorithm proposed by Chen, et al. [9], nodes decide whether to be active or not based on two-hop neighborhood information: a node is eligible as leader if two of its neighbors cannot reach each other either directly or via one or two leaders. Eligible nodes decide whether to become leaders based on a randomized algorithm, where the probability of being elected depends on the *utility* of the node (which can be informally understood as the number of additional pairs of nodes that would be connected if the node were to be elected leader) and on the amount of energy remaining in the node's battery. The CPC strategy presented in [34] is based on the construction of a connected dominating set: nodes in the dominating sets are the representatives, and coordinate the sleeping periods of the other units. Routing equivalence is ensured by the fact that, by the definition of dominating set, every node in the network has at least one leader node as immediate neighbor, and by the fact that the nodes in the dominating set are connected.

A different notion of node equivalence is used in [33]: two nodes are equivalent if they are able to cover a given subregion of the deployment area. This definition is suited to wireless sensor networks, whose goal is to monitor a certain geographical region. In this model, every sensor covers a circular area of radius r_c, and the monitored area R is covered if every point of R is at distance at most r_c from at least one node. The goal is to alternately turn sensors on and off (in this case, it is the sensing apparatus of the node that is turned on and off) in such a way that coverage of the deployment area is always guaranteed. The authors propose a centralized heuristic to determine a maximal number of mutually exclusive subsets of sensors, with the property that the sensors in every subset guarantee network coverage. If this number is k, the network lifetime could be extended in principle by a factor of close to k.

Cooperative strategies rely on a homogeneity assumption on the node transmitting ranges (or, in the case of coverage, on the node sensing ranges), namely, that all the nodes have the same range r, which can be intended as the maximum range. This assumption is vital in the GAF strategy, since the value of r is used to determine the size of the cells used to partition the deployment region. SPAN and CPC are based on neighborhood relationships between nodes and, in principle, could work also if the homogeneity assumption does not hold. However, it should be observed that routing cooperative strategies are effective only when the communication graph is very dense, and many disjoint paths exist between source-destination pairs. If this is not the case, several nodes will remain active for a long time, thus reducing considerably the energy savings achieved by the strategy. Hence, the assumption that all nodes transmit at the maximum range r is also essential for SPAN and CPC in practice.

Contrary to cooperative strategies, topology control techniques leverage the capability of nodes to vary their transmitting ranges dynamically, in order to reduce energy consumption. In fact, the power needed to transmit data depends on the sender-receiver distance. More precisely, the power p_i required by node i to correctly transmit data to node j must satisfy inequality

$$\frac{p_i}{\delta_{i,j}^{\alpha}} \geq \beta \ , \qquad (1)$$

where $\alpha \geq 2$ is the *distance-power gradient*, $\beta \geq 1$ is the *transmission quality* parameter, and $\delta_{i,j}$ is the

Euclidean distance between the nodes. While β is usually set to 1, α is in the interval $[2, 6]$, depending on environmental conditions [28]. A simple (but widely adopted) energy model can then be devised by simply turning (1) into an equality. According to this, if a node transmits at distance, say, $\frac{r}{2}$ and $\alpha = 4$, it consumes $\frac{1}{16}$ of the energy required to transmit at full power.

Observe that (1) refers to the transmit power only, and it does not account for the power consumption of other components of the wireless transceiver. Thus, the energy savings achieved in a realistic setting might be considerably different than predicted by 1. This point will be discussed in detail in the remainder of the paper.

Several topology control protocols have been recently proposed in the literature [3, 6, 8, 16, 20, 21, 27, 29, 36]. They differ in the type of topology generated, and in the way it is constructed. Usually, the resulting communication graph is rather sparse and can be easily maintained in the presence of node mobility. Having a sparse communication graph has the further advantage of making the task of finding routes between nodes easier, since there are relatively few paths between source-destination pairs. For a survey on topology control, the reader is referred to [26].

3 A framework for comparison

In this section, we define a framework for the comparison of cooperative and topology control techniques, which will be used in the remainder of this paper. The framework is *unified* since we make the same assumptions (to the extent to which this is possible[2]), especially on what concerns the traffic and the energy models adopted. To define the framework, we use an approach inspired by the idealized model in [5] to investigate the lifetime/density tradeoff in cell-based cooperative strategies.

3.1 The cooperative strategy

In evaluating cooperative strategies, we choose to focus on cell-based techniques, since they appear as the most promising. In [37], it is shown by means of simulations that GAF (which is the only cell-based strategy presented to date) increases network lifetime, with the amount of increase dependent on node density and mobility. When the density is increased by a factor of four, network lifetime becomes a factor of 2–4 times longer for different variants of GAF, i.e., the lifetime extension scales roughly linearly with node density. This behavior is confirmed by the theoretical and experimental analyses presented in [5], which considers an idealized cell-based strategy, where the traffic is evenly distributed over the cells, and the cost (expressed in terms of messages exchanged) of the leader election algorithm is neglected. By contrast, SPAN does not seem to scale as well with node density. For SPAN, the overhead required for node coordination tends to increase rapidly with node density, partly because it can not take advantage of the rich structural information assumed in cell-based approaches. This increasing overhead for coordination counterbalances the potential savings achieved by the increased density. The experimental results presented in [9] show that SPAN increases network lifetime significantly (by a factor ranging from 2 to 2.5), but that this increase is almost independent of node density. Less quantitative information is known about CPC. In [34], it is shown that CPC reduces node energy consumption by a factor of 0.12–0.14, but no energy savings vs. node density analysis is presented.

We will use the following idealized model to analyze the performance of cell-based strategies.

a1. n nodes are distributed uniformly at random in $R = [0, 1]^2$;

a2. R is divided into $C = \left\lceil \frac{2\sqrt{2}}{r} \right\rceil^2$ non-overlapping square cells of equal side (not greater than $\frac{r}{2\sqrt{2}}$), where r is the nodes' transmitting range;

a3. nodes can communicate directly when they are at distance at most r, i.e., there exists the bidirectional link (i, j) in the communication graph if and only if $\delta_{i,j} \leq r$;

a4. r is set to the minimum value of the transmitting range that ensures that the communication graph is connected with high probability;

a5. The overhead required for node coordination is ignored.

In view of Assumption *a5.*, the energy savings derived in the following can be seen as the best possible any cooperative strategy can achieve. Assumption *a4.* is motivated by the fact that, in principle, the nodes' transmitting range should be set to the minimum value that makes the communication graph connected, known as the *critical transmitting range*. When the transmitting range is set to the critical value, the network capacity is maximal and the node energy consumption is minimal [13, 15, 19, 22]. Although computing the critical value in a distributed manner is feasible [22], it is quite common to characterize it using a probabilistic approach, i.e., determining the value r of the transmitting range that ensures connectivity with

[2]Clearly, some assumptions are simply not relevant for the topology control setting.

high probability (w.h.p.) [14, 23, 31]. In this paper, we will follow this probabilistic approach (see Section 4 for details).

3.2 The topology control protocol

The performance of the idealized cell-based strategy described above will be compared to that of a topology control protocol that computes the Minimum Spanning Tree (MST) of the network. The protocol is idealized, since we assume that the MST is computed with zero cost (in terms of messages exchanged). This assumption is the counterpart of assumption *a5.* of cell-based strategies.

The choice of the MST as the "best possible" topology generated by a topology control protocol is motivated by the following considerations. First, it has been shown that the range assignment induced by the MST (see Section 4 for details on how this range assignment is defined) is at most twice the energy optimal range assignment [18]. However, the average-case approximation ratio is much better: around 1.04–1.06, according to the simulation results presented in [2]. Considering that computing the energy optimal range assignment on networks of moderate size ($n > 40$) is virtually impossible, due to the intractability of the problem [10, 18], the MST can be considered as the best possible topology in practical scenarios. This statement is confirmed by the theoretical result presented in [35], where it is shown that the MST is a broadcast spanner of the communication graph G obtained when all the nodes transmit at the maximum range r. In words, this means that the difference between the minimum energy required to broadcast a message in G and that required to broadcast a message using the MST is at most a constant factor; i.e., the MST is a good broadcast tree for practical purposes.

A weak point of MST is that its computation requires global knowledge (e.g., the position of all network nodes), which can be a major problem in real life networks. However, more practical (i.e., localized) topology control protocols, such as the k-NEIGH protocol of [6], have been proven to have performance close to that of MST. Thus, instead of committing to a particular protocol, we opted for investigating the "best possible" performance of topology control techniques, being confident that this performance can be at least closely matched in realistic scenarios.

The MST can be seen as the extreme case of topology control, in which the communication graph is reduced to the "thinnest" (and, in one sense, most energy efficient) structure that maintains the nodes connected. However, when the communication graph is very sparse, there will be few paths connecting source/destination pairs: in particular, in the MST there is only one path between any source/destination pair. In this situation, it is very likely that multi-hop traffic generates a poorly balanced load among the nodes. Thus, choosing a less energy efficient topology, but one that balances load better than MST, is likely to be preferred in practice.

3.3 Multi-hop traffic generation

A common approach to generate multi-hop traffic in ad hoc networks is to choose a number of source/destination pairs at random, and to send ConstantBitRate (CBR) traffic from the sources to the destinations, where the paths connecting the sources and destinations are chosen according to some routing protocol. Usually, the number of source/destination pairs considered is quite limited (in the order of 5–10), even when the number of nodes in the network is quite large (in the order of 100). Another common assumption is that the source/destination pairs remain fixed during the entire simulation time.

An alternative strategy, which is tailored to the WSN scenario, is to have a fixed data collection site, which is usually situated on the boundary of the deployment region; the (sensor) nodes generate CBR traffic directed to the collection site. In this case, multi-hop traffic is generated when a node can not reach the collection site directly.

In this paper, we will use a different approach to generate multi-hop data traffic. The basic idea is to compute the average load generated on every node when a (possibly) multi-hop message circulates in the network. To this purpose, every node maintains two counters S and R, which store the number of messages sent and received by the node. For every source/destination pair (s, d), we compute the most energy-efficient path $P_{sd} = \{s, u_1, \ldots, u_k, d\}$ that connects them. Under the assumption that transmissions are perfectly scheduled, i.e., that no collision to access the wireless channel occurs, exactly $k+1$ transmissions are needed to communicate a message from s to d. We repeat this process for every possible source/destination pair in the network. Let S_i and R_i be the values of the counters at node i (it is easy to prove that $R_i = S_i$) at the end of the computation; dividing these values by the number $n(n-1)$ of all possible source/destination pairs, we obtain the average number of send and receive operations performed by node i when a (possibly) multi-hop message circulates in the network, under the assumption that all the source/destination pairs are equiprobable. So, the average load of node i when C multi-hop messages are transmitted in the network is equal to $C\frac{S_i}{n(n-1)}$ send and $C\frac{R_i}{n(n-1)}$ receive operations.

We stress that the above scheme (that uses energy efficient routes) is only used to generate average node loads, and does not prevent our approach from being used with any routing protocol. Furthermore, our approach can be easily adapted to the case of non-uniform probability distributions on the source/destination pairs.

Our traffic model is representative of a scenario in which there are relatively many active source/destination pairs, and these change frequently during the network operational time. With respect to this scenario, we believe our model is an improvement over the commonly used technique of using few and time invariant flows. Our model is also compatible with a WSN scenario in which the data collection site is mobile; e.g., the data collection site is a ranger equipped with a PDA who moves in a natural park monitored by sensors.

3.4 The energy model

A major difficulty in defining the energy model in case of 802.11 based ad hoc networks is due to the fact that the measurements of the wireless interface energy consumption reported in the literature consider only the maximum transmit power. This is the case, for instance, in the already mentioned measurements reported in [12, 37]. On the other hand, topology control protocols are based on the ability of the wireless node to dynamically adjust its transmitting range. This feature is actually available on several commercial 802.11 wireless cards. For instance, the Cisco Aironet 350 card can use six different transmit powers, ranging from 1mW to 100mW. Note that the transmit power levels reported in the data sheets of the card refer to the power consumption of the RF amplifier only, and not to the entire wireless interface. To the best of our knowledge, the only measurements that account for different transmit power levels are those reported in [11], which refer to a Cisco Aironet 4800 wireless card. This card allows different values for the transmit power level, ranging from 1mW to 50mW. The measured energy consumption of the card in the different states is $sleep : idle : rx : tx_{min} : tx_{max}$=0.056 : 1 : 1 : 1.044 : 1.418, when the data rate is 1Mb/sec.

Given the discussion above, it seems reasonable to assume that the energy consumption of a 802.11 wireless interface when the transmit power is minimum is comparable to the energy consumption in idle or receive state. The situation is different in case of WSN, where the sensor nodes usually utilize short range radios. For instance, the measurements reported in [25], which refers to a Medusa II sensor node, show $sleep : idle : rx : tx_{min} : tx_{max}$ ratios of 0.440 : 1 : 1.006 : 0.872 : 1.114, where tx_{min} corresponds to a transmit power of 0.0979mW, and tx_{max} to a power of 0.7368mW. The measurements refer to a data rate of 2.4Kb/sec. There are two major differences between the energy consumption ratios in the 802.11 and WSN scenario:

- the power consumption in the sleep state is considerably higher in the WSN than in the 802.11 scenario. This is due to the fact that, while the measurements in case of 802.11 cards refer to the energy consumption of the wireless interface only, in case of WSN what is reported is the energy consumption of the entire node. The value of 0.440 for the Medusa II node refers to the scenario in which the radio is turned off, but the processor and the sensing apparatus of the node continue to operate. This is coherent with our goal of comparing cell-based and MST-based techniques, which are only concerned with reducing the energy consumed to communicate.
- in the WSN scenario, the energy consumed to transmit at minimum power is lower than that consumed to receive, or to listen the wireless channel (idle state). This means that nodes that reduce their transmitting range significantly will actually consume substantially less energy transmitting than they will receiving or listening. Thus, nodes that transmit a lot might actually live longer than nodes that do not transmit often. This point, which is quite counter-intuitive, will be carefully investigated in our simulations.

4 Simulation setup

In this section, we discuss some details of our simulation setup, including: (a) node placement, (b) routing, (c) traffic generation, (d) energy consumption, (e) simulation time period, and (f) network lifetime definition. These applies to both the stationary and the mobile scenario; the specific issues that are relevant to the mobile setting only will be dealt with in Section 6.

Node placement. The simulator distributes n nodes in the deployment area $R = [0, 1]^2$. All the nodes have the same energy E_{init} initially available. The node energy consumption is calculated as follows. We consider three different scenarios: no energy saving (NES), cell-based (CB) and MST. In the NES and CB scenario, the nodes' transmitting range is set to the critical value r for connectivity (see Assumption *a4*). For a given placement of the nodes, the critical transmitting range corresponds to the longest edge of the Euclidean MST built on the nodes [24, 30]. However, in many situations node placement is not known in advance, and the critical transmitting range must be characterized in a probabilistic way [14, 23, 31]. If only probabilistic information about node positions is known, the value of r can be determined considering the empirical distribution of the longest MST edge over a large set of experiments. In our experiments, we have defined r as the 0.99 quantile[3] of this distribution, under the assumption that nodes are distributed uniformly at random in R. Table 1 reports the values of the critical transmitting range (calculated over a set of 10000 experiments) for the different values of n used in our simulations. These values of r are used to define the desired cell size in the CB scenario.

n	r	n	r
10	0.65662	250	0.15333
25	0.44150	500	0.10823
50	0.32582	750	0.08943
75	0.27205	1000	0.07656
100	0.23530		

Table 1: Values of the critical transmitting range r for different values of n.

For a given placement of the nodes, we build the communication graph as follows:

- in the NES and CB scenario, we insert a bidirectional edge (i, j) whenever nodes i and j are at distance at most r (see Assumption *a3*);

- in the MST scenario, we first build the MST on the n nodes. Then, we set the transmitting range of node i to $\max_{(i,j)\in MST} \ \delta_{i,j}$, i.e., to the maximum range needed to reach a neighbor of i in the MST. Observe that, in principle, $\max_{(i,j)\in MST} \ \delta_{i,j}$ can be larger than the critical range r. However, given our definition of r, this occurs with very low probability. Once the value of the transmitting range for every network node has been computed, we define the communication graph as follows: edge (i, j) is in the communication graph if and only if $r_i \geq \delta_{i,j}$ and $r_j \geq \delta_{i,j}$. In other words, we consider only bidirectional wireless links. In principle, the communication graph generated in this way might contain edges that do not belong to the MST. However, this occurs very infrequently.

An example of the communication graph generated by the MST is shown in Figure 1–b. Figure 1–a shows the communication graph on the same set of nodes in the NES/CB scenario.

[3]We recall that the q quantile of a series of data gives the point such that $100q$ percent of the data lie before.

Routing. In general, in the NES/CB scenario there exist several paths with minimal energy consumption for a given source/destination pair (s, d). In fact, the nodes use the same transmitting power, and any path connecting s and d with minimum hop count is optimal from the energy efficiency point of view. Thus, we must define a strategy to route the messages from the source to the destination in this scenario. In our simulation, we have implemented a cell-based routing algorithm, which can be seen as an instance of the widely studied class of geographical routing algorithms.

The cell-based routing algorithm is defined as follows. Given the communication graph G, we build a *cell graph* CG by inserting one node for every non-empty cell. Then, we insert the bidirectional edge (i, j) in CG if and only if there exist nodes u, v in G such that $u \in C_i$, $v \in C_j$, and $(u, v) \in G$, where C_i (resp., C_j) denotes the cell to which node i (resp., j) corresponds. For any node x, let i_x denote the node that corresponds to the cell to which x belongs. Now, for any source s, we compute one possible single source shortest path tree rooted at i_s[4], by selecting at random the node to be expanded next, among those eligible, in the classical Dijkstra's algorithm. We then use such tree for all the messages originating at s.

Note that the cell-based routing algorithm defined above does not specify completely the path from the source to the destination: nodes in the same cell are perfectly equivalent from the routing algorithm's point of view, thus capturing the intuition upon which the cell-based strategy is founded. Indeed, the routing algorithm, as defined here, does not account for possible intra-cell communications needed to transmit/receive the message to/from the current leader node. In other words, we make the following assumption, which is coherent with our idealized setting: node states and transmissions are perfectly scheduled, i.e., when a node is scheduled to transmit/receive, it is also active.

Traffic load. We first compute the cell load by assigning the S and R counters (see Section 3.3) to every cell in CG. For every source/destination pair (s, d) in G, we select the path in CG that connects the corresponding cells using the routing algorithm specified above and update the counters accordingly. The load of each cell C_i is then equally subdivided among the $n_i \geq 1$ nodes in it. In other words, we assume that the routing algorithm is "smart", and that it perfectly balances the load between the nodes in the same cell. Again, this assumption is coherent with our idealized setting.

In case of the MST, the evaluation of the per node load is simpler because the minimum energy path

[4]There can be exponentially many such trees, given the unit length of the edges.

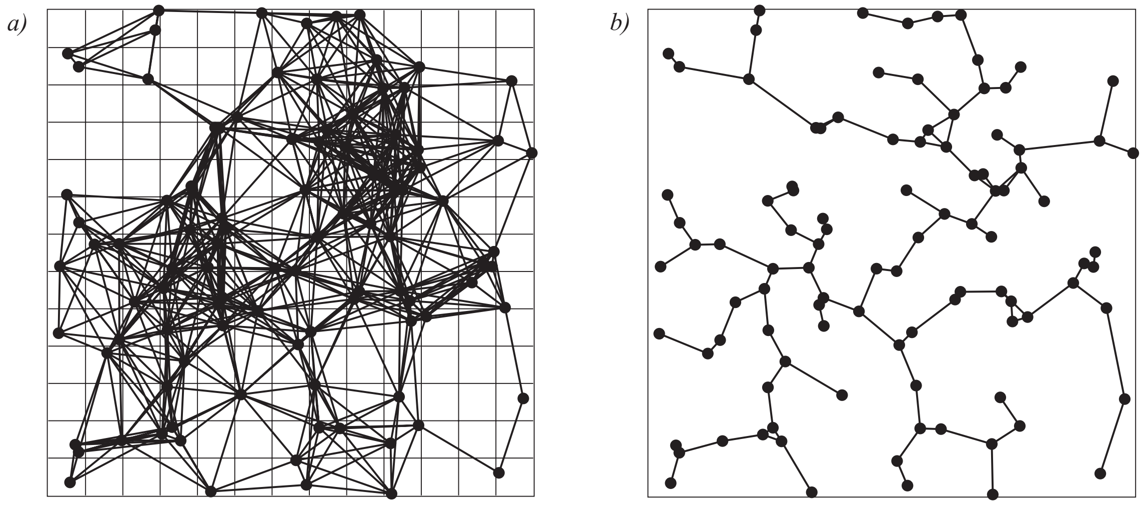

Figure 1: Communication graphs in the NES/CB scenario (left) and in the MST scenario (right).

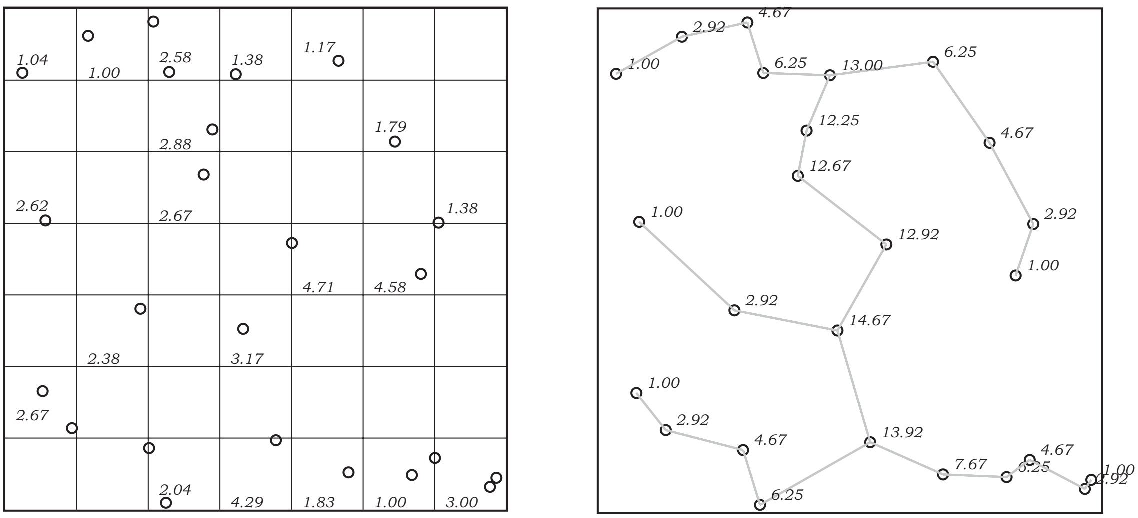

Figure 2: Load generated when $n = 25$ multi-hop messages are circulating in a network composed by n nodes in the NES/CB scenario (left) and in the MST scenario (right).

that connects any source/destination pair is unique.

In both cases, the load is then normalized with respect to the total number of source/destination pairs, and multiplied by n (i.e., we assume that n multi-hop messages are generated in the network). An example of the per node load generated in the NES/CB and MST scenario when $n = 25$ is shown in Figure 2. The numbers refer to the values of the S and R counters. As expected, when the same number of multi-hop messages circulate in the network, the traffic generated in the MST is much higher than in the NES/CB scenario. This is due to the fact that the average hop distance between source/destination pairs is much larger in the MST than in the communication graph used in the NES/CB scenario. For instance, in the example shown in Figure 2, a total of 48.18 messages are generated in the NES/CB scenario, while 150.38 messages are generated in case of the MST. The average hop distance between source and destination of a message is 1.92 in the NES/CB scenario, and it is 6.01 in case of the MST. This results in a maximum per node load of 4.71 send (and receive) operations in the NES/CB scenario, and of 14.67 send/receive operations in the MST case.

Energy consumption. This is clearly a crucial aspect, given the goal of our simulations. However, to reduce the complexity of the experiments, we need to make the following simplifying assumptions.

1. We assume perfectly scheduled transmissions, and hence that every send and receive operation lasts one time unit.

2. (Applies to NES only.) We assume that the routing algorithm is able to distribute the traffic load of one cell among the nodes in that cell evenly.

3. (Applies to CB only.) We assume that the cell-based strategy schedules the active and sleeping periods of the nodes in a cell in a perfectly balanced way.

4. We consider time invariant traffic load.

Admittedly, these may affect the significance of the *absolute* figures obtained. While this is clearly a point that deserves more investigations (see also Section 7), we observe that here we are primarily interested in the *relative* values of network lifetime extensions.

Let us first consider the NES scenario. Let $L_i = S_i + R_i$ be the overall load of the cell C_i, and let n_i be the number of nodes in C_i. By Assumption 1, cell C_i will take L_i time units to handle the traffic. Let us consider a period of time T, with $T > L_i$ (we discuss how to set T later). By Assumption 2, every node in C_i spends $\frac{L_i}{n_i}$ units of time sending or receiving messages. The amount of energy consumed by a node $u \in C_i$ in this period is $\frac{rx \cdot R_i + tx_{max} \cdot S_i}{n_i}$, where rx is the energy needed to receive a message and tx_{max} is the energy needed to send a message at distance r.[5] In the remaining time $T - \frac{L_i}{n_i}$ of the period, the node remains idle, consuming 1 unit of energy per time unit. Thus, the energy consumption of node u during the period T is $E_u^{NES} = T - \frac{L_i}{n_i} + \frac{rx \cdot R_i + tx_{max} \cdot S_i}{n_i}$. Dividing this value by T, we obtain the average energy consumption per time unit of node u during the period T. In view of Assumption 4, the average energy consumption per time unit can then be used to compute the lifetime of node u.

Let us now consider the CB scenario. By Assumption 4, every node in cell C_i sleeps for a fraction $(1 - \frac{1}{n_i})$ of the time period T. During this time, any node $u \in C_i$ has an energy consumption of $sleep \cdot (1 - \frac{1}{n_i})T$. In the fraction $\frac{T}{n_i}$ of the period node u is active, and spends $\frac{L_i}{n_i}$ units of time sending/receiving, consuming $\frac{rx \cdot R_i + tx_{max} \cdot S_i}{n_i}$ units of energy. In the remaining $\frac{T - L_i}{n_i}$ units of time, the node is idle, consuming $\frac{T - L_i}{n_i}$ units of energy. Thus, the energy consumption of node u during the period T is $E_u^{CB} = sleep \cdot (1 - \frac{1}{n_i})T + \frac{rx \cdot R_i + tx_{max} \cdot S_i}{n_i} + \frac{T - L_i}{n_i}$. As in the previous case, we divide this value by T, obtaining the average energy consumption per time unit which will be used to evaluate the lifetime of node u.

Finally, let us consider the MST scenario. Let S_u, R_u be the load of node u, and let us consider a period of time T as above. The node requires $L_u = S_u + R_u$ time units to handle the traffic, consuming $rx \cdot R_u + f(r_u) \cdot S_u$ units of energy. Here, r_u is the transmitting range of node u, and $f(r_u)$ is defined as follows: $f(r_u) = tx_{min} + (tx_{max} - tx_{min}) \cdot (r_u/r)^2$. With this definition, we have $f(0) = tx_{min}$ (energy consumed to send a message at minimum transmit power), and $f(r) = tx_{max}$ (when the transmitting range is set to the critical value r, the unit consumes energy tx_{max} to send a message). In the remaining time $T - L_u$, node u remains idle, consuming $T - L_u$ units of energy. Thus, the energy consumption of node u during the period T is $E_u^{MST} = rx \cdot R_u + f(r_u) \cdot S_u + T - L_u$.

Simulation time period. The value of T is set as follows. Let $\bar{L}_i$ be the average per cell load in the NES/CB scenario; T is set to $k \cdot \bar{L}_i$, where k is a parameter that accounts for the network load. For instance, setting k to 10 corresponds to considering a network in which (on the average) a cell spends 10% of the time in communications.

Network lifetime. We have used three different

[5] Without loss of generality, we assume that the power needed to transmit a message at distance r is the maximum transmit power.

definitions of network lifetime, which are representative of notions of lifetime commonly used in the literature and which account for the number of alive nodes and for connectivity.

Definition 1. *Network lifetime is defined as:*

1D: *the time for the first node to die;*

DISC: *the time to network disconnection;*

90LC: *the time for the size of the largest connect component to drop below* $0.9n$.

Before concluding this section, we give a numerical example of the node energy consumption computed according to the traffic and energy models described above in different situations. Let us consider an 802.11 ad hoc network scenario, in which, we assume the power ratios from [11], i.e. $sleep : idle : rx : tx_{min} : tx_{max}$ ratios equal to $0.056 : 1 : 1 : 1.044 : 1.418$. Suppose node u belongs to cell C_i, with $n_i = 3$, and assume $S_i = R_i = 5$. Let us set k to 20, which corresponds to a 5% average load scenario. We have $T = 100$, and the energy consumption per time unit is 1.007 in the NES scenario, and 0.377 in the CB scenario. Suppose that the load of node u in the MST scenario is $S_u = R_u = 12$, and that $r_u = \frac{r}{2}$. With these settings and the same value for T, we obtain an energy consumption per time unit of 1.016. Setting $k = 5$ (20% average load) yields an energy consumption per time unit of 1.028, 0.398, and 1.064 in the NES, CB, and MST scenario, respectively. As expected, a higher load causes an increased energy consumption. Note that the energy consumption in the MST is slightly higher than in the NES scenario, and that considerable savings are achieved only with the cell-based approach. The situation is quite different if we consider the $sleep : idle : rx : tx_{min} : tx_{max}$ ratios of the WSN node reported in [25], i.e., $0.440 : 1 : 1.006 : 0.872 : 1.114$.[6] In this case, the energy consumption per time unit of node u when the average load is 5% is 1.002, 0.628 and 0.992 in the NES, CB and MST scenario, respectively. If the average load is 20%, the energy consumption is 1.008, 0.635 and 0.969, respectively. It is interesting to note that, in the MST scenario, an increased traffic load results in a decreased energy consumption.

5 Stationary networks

In this section, we report the experimental results obtained in stationary networks. The goal of our experiments is to answer the questions below.

[6]In what follows, we refer to these values as the "WSN scenario", although we acknowledge this is a single data point from one particular sensor node and does not necessarily represent accurate data for *all* types of nodes.

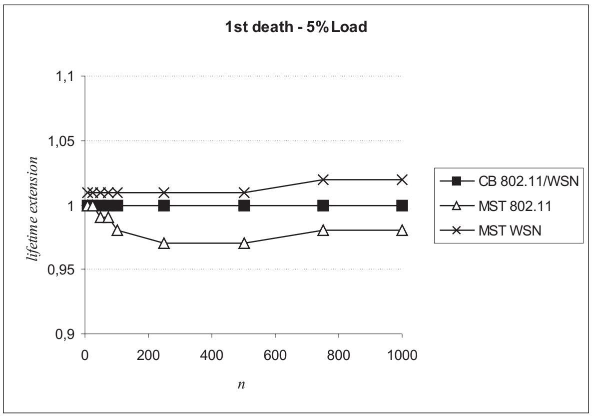

Figure 3: Lifetime extension for the CB and MST approach, for increasing values of n. The lifetime extension is expressed as a multiple of the lifetime in the NES scenario. The average load is 5%.

- Given the same "minimal" node density for connectivity, which one between cell-based and MST is more effective in extending network lifetime?
- How does the lifetime extension achieved by the two techniques scale with the node density?

5.1 Lifetime with minimum density

In the first set of experiments, we have evaluated network lifetime in the NES, CB and MST scenarios under the hypothesis that the node density (hence the node number) is the minimum required to obtain connectivity w.h.p. as a function of the critical transmitting range[7]. The actual values of n considered range from 10 to 1000 (see Table 1).

For each scenario, we have considered three values of the average load (5%, 10% and 20%), and two energy models (802.11 and WSN). The results of our simulations for 5% and 20% average load when network lifetime is defined as 1D, averaged over 1000 experiments, are reported in Figures 3 and 4.

A few remarks are in order.

- In case of low load (5%), CB and MST provide little extensions with respect to NES. MST is even detrimental from the energy consumption point of view in the 802.11 scenario. This is due to the fact that, as outlined above, the MST provides poor load balancing among the nodes.
- When the load is relatively high (20%), the MST performs significantly better than NES,

[7]The actual process is clearly reversed; that is, for each value of n we compute the minimum transmitting range that ensures connectivity w.h.p., and set r to that value.

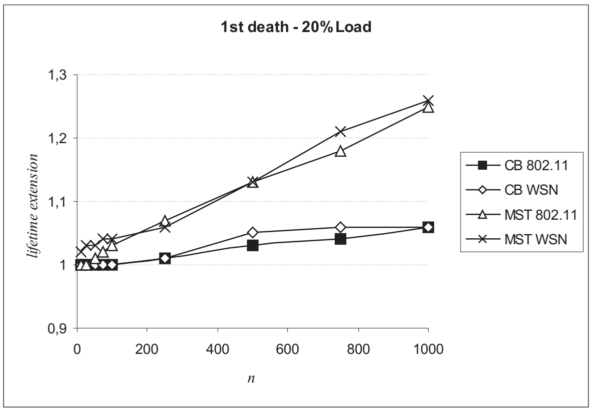

Figure 4: Lifetime extension for the CB and MST approach, for increasing values of n. The lifetime extension is expressed as a multiple of the lifetime in the NES scenario. The average load is 20%.

providing lifetime extensions that increase with n, up to a factor 1.25. CB improves as well, but more moderately.

– MST provides better performance than CB under both load conditions when the WSN energy model is used.

The fact that both CB and MST provide relatively better performance with high network load merits some discussion. The relative improvement in case of CB is due to the fact that the difference between the energy consumption of a node u in NES and CB scenarios is given by $\frac{E_u^{NES} - E_u^{CB}}{T} = \left(1 - \frac{1}{n_i}\right)(1 - sleep)$, i.e., it is independent of the cell load. Since the absolute value of the network lifetime is reduced with a higher load, and the relative advantage of CB over NES remains the same, the lifetime extension provided by CB with respect to NES in absolute terms increases with network load. In case of MST, the better performance in presence of high load is due to the fact that nodes in NES transmit at maximum power; thus, the large number of send operations generated in the 20% load scenario induces a better relative performance of the MST.

We have repeated the same experiments considering the other definitions of network lifetime. With DISC we obtained essentially the same results as in case of 1D. This is due to the fact that, both in CB and MST, the network is very likely to become disconnected as soon as the first node dies. With CB energy conservation, nodes are likely to die in groups (with those in the less populated cells first). Since in the minimum density scenario many cells are expected to contain only one node, it follows that the death of the nodes in the first set will very likely disconnect the network. In case of the MST, the communication graph is extremely sparse, and the death of a single node will most likely disconnect the network.

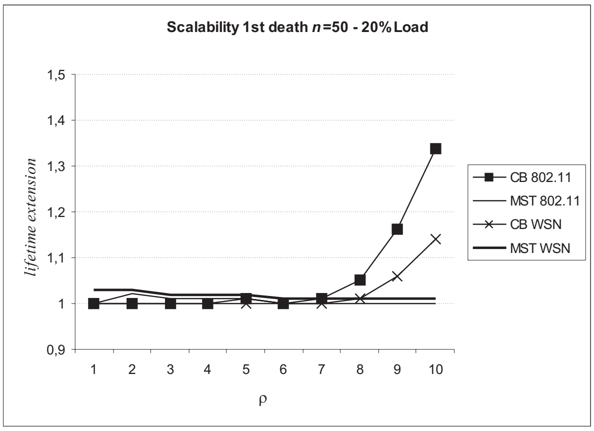

Figure 5: Lifetime extension for increasing values of the node density ρ. Network lifetime is defined as the time for the first node to die, and is expressed as a multiple of the lifetime in the NES scenario.

The situation is slightly different when we consider the 90LC definition of lifetime. The results of these simulations, which are not reported for lack of space, show that both CB and MST provide only marginal savings with respect to NES in every scenario considered (low and high load, 802.11 and WSN energy model), the maximum being a factor 1.02 (for MST with 20% load and the WSN energy model).

5.2 Lifetime for increasing density

In the second set of experiments, we have investigated how the lifetime extension achieved by CB and MST scales with node density, relative to the minimum density scenario with $n = 50$ (hence with $r = 0.32582$, see Table 1). Then, we have increased node density by distributing ρn nodes and leaving the value of the transmitting range, and consequently also the cell size, unchanged. As the expected number of nodes in a cell is ρ times that of the minimum density scenario, the CB strategy is likely to achieve better energy savings as ρ increases. In case of the MST, we simply computed the MST on the set of nodes as in the previous experiments. In this situation, the advantage of having a higher node density is that the transmitting range r_i of a generic node i is likely to be smaller than in the minimum density scenario. Thus, since $r = 0.32582$ independently of the node density, the node lifetime is, in general, longer (in absolute terms) than in the case of minimum density. However, this does not necessarily correspond to better energy savings, as the network lifetime in the NES

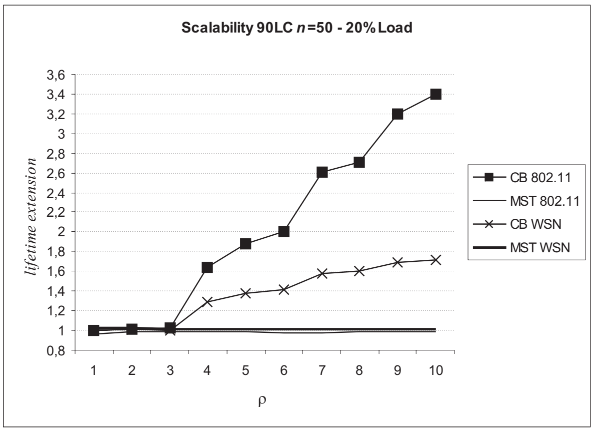

Figure 6: Lifetime extension for increasing values of the node density ρ. Network lifetime is defined as the time for the size of the largest connected component to drop below $0.9n$, and is expressed as a multiple of the lifetime in the NES scenario.

scenario might be longer as well.

We have considered values of ρ ranging from 1 to 10. For each value of ρ, we have evaluated the network lifetime achieved by CB and MST using the three different notions of network lifetime in Definition 1. As before, we have used three values of the average load (5%, 10% and 20%), and two energy models (802.11 and WSN). The results for 1D and 90LC when the load is 20%, averaged over 1000 simulation runs, are shown in Figures 5 and 6. Again, the results obtained using the DISC lifetime definition are not reported, since they match closely those obtained with 1D.

We remark that:

- the lifetime extensions achieved by MST do not scale with node density.
- The extensions achieved by CB show a certain degree of scalability, especially when the 802.11 energy model is used. In this case, the lifetime approaches 1.33 (respectively 3.4) times the lifetime in the NES scenario under definition 1D (respectively, 90LC). Note, however, that these results refer to a very high density case (10 times the minimum density).

The simulation results for different values of the load, which are not reported for lack of space, show that the average load has negligible influence on the performance of both CB and MST as the node density increases.

6 Mobile networks

In this section, we investigate the effects of mobility on the performance of the CB and MST energy saving techniques.

Let us first consider the CB approach. One of the major limitations of this technique in stationary networks is the "staircase behavior": many nodes die simultaneously at well defined time intervals. In case of node mobility, it is likely that the staircase behavior is significantly reduced: as nodes move, they are likely to pass through highly and scarcely populated cells. Thus, energy consumption is better balanced among the network nodes, and a positive effect on network lifetime is to be expected. However, it is also important to note that the critical transmitting range in presence of node mobility is in general different from that of stationary networks: for instance, in [31] it is shown that the critical transmitting range must be increased by about 20% with respect to the stationary case if connectivity must be ensured during the entire lifetime of a mobile network. On the one hand, this increase has a damaging effect to lifetime, since it causes a higher node energy consumption. On the other hand, the increased transmitting range induces also a larger cell size, and, consequently, a larger expected number of nodes per cell with respect to the stationary scenario. A priori, it is thus difficult to evaluate the net effect of node mobility on network lifetime; investigating this tradeoff was precisely one of the goals of our simulations.

We assume that nodes move according to the random waypoint (RWP) model [17], which we now briefly recall. Every node chooses uniformly at random a destination in $[0,1]^2$ and moves towards it along a straight line with a velocity chosen uniformly at random in the interval $[v_{min}, v_{max}]$. When the node reaches the destination, it remains stationary for a predefined pause time t_{pause} and then starts moving again according to the same rule.

Let r and r_m denote the critical transmitting range in stationary and RWP mobile networks, respectively. It is known [32] that $r_m \geq r$ (asymptotically, for $n \to \infty$) in general, and that $r_m \gg r$ when $t_{pause} = 0$, where $r_m \gg r$ means that $\lim_{n\to\infty} \frac{r}{r_m} = 0$. The increased transmitting range in presence of RWP mobility is due to the phenomenon known as *border effect* [4, 7]: RWP mobile nodes tend to concentrate in the center of the deployment region R. In turn, this is due to the fact that in the RWP model a node chooses a uniformly distributed destination point rather than a uniformly distributed angle. Therefore, nodes located at the border of R are very likely to move back towards the middle of the region. The intensity of the border effect mainly depends on t_{pause}. In fact, a longer pause time tends to increase the percentage of nodes that are "resting" at any given time. Since the starting and destination points of a movement are chosen uniformly in R, this implies that a relatively long pause time generates a "more uniform" node spatial distribution.

Let us now consider the MST approach. In this case, the lifetime of a generic node i is determined by its transmitting range r_i. Due to node mobility, the value of r_i varies with time, and the expected node lifetime depends on the average value of r_i during the node operational time. Since characterizing this average value analytically is difficult, the effect of mobility on MST-based energy conservation is once more not clear, and it will be investigated through simulation.

6.1 Simulating mobile networks

As in the case of stationary networks, we have first considered the minimum density scenario, and then investigated how the performance provided by the two approaches scales with node density.

We have modified the simulator for stationary networks in order to support RWP node mobility. We have then generated a large set of RWP node distributions, by moving n nodes, for $n = 10, 25, 50, 75, 100, 250, 500$, for a considerable number of steps. This data set has been used to evaluate the critical transmitting range r_m in presence of mobility, and the cell load in the NES/CB scenario, according to the procedure described in the Section 4 (traffic load). We remark that here the load of cell C_i is evaluated off line, by averaging over a large set of RWP node distributions. This choice is motivated by the fact that computing the cell load during the simulation of a mobile network requires a prohibitive running time. Observe that, due to the border effect caused by RWP mobility, boundary cells will be in general much less loaded than central cells.

In case of MST, we have assumed that the load of the entire network is evenly distributed among the nodes, where the overall load is calculated using the RWP node distributions as input set. Again, this choice is motivated by computational concerns, and by the fact that it is reasonable to assume that in a mobile network that remains operative for a relatively long period of time the load is well balanced.

In principle, the energy consumption of node u at time t should be computed as a function of the number $n_{u(t)}$ of nodes in the same cell of node u at time t, or as a function of the node transmitting range $r_{u(t)}$ at time t. However, computing node energy consumption "instantaneously", besides being quite complicated to be implemented in the simulator, would be scarcely indicative of a realistic mobile scenario, in which the information available to the nodes is not always up to date. For this reason, we have decided to compute nodes' energy consumption every $\bar{T}$ units of time. In the NES scenario, the energy consumption per unit of time of node u during the time interval $[t, t+\bar{T})$ is set to

$$e_u^{NES} = \frac{T - \frac{L_{u(t)}}{n_{u(t)}} + \frac{rx \cdot R_{u(t)} + f(r_m) \cdot S_{u(t)}}{n_{u(t)}}}{T} ,$$

where T is defined as a function of the average load, as described in Section 4, $L_{u(t)}$, $S_{u(t)}$ and $R_{u(t)}$ represent the load of the cell where u was at time t, $n_{u(t)}$ is the number of nodes in the same cell at time t, r_m is the critical transmitting range in RWP mobile networks, and f is defined as in the paragraph on "Energy consumption" of Section 4. Similarly, the energy consumption per unit of time in the CB is approach is defined as

$$e_u^{CB} = \frac{sleep \cdot (1 - \frac{1}{n_{u(t)}})T}{T} + \frac{\frac{rx \cdot R_{u(t)} + f(r_m) \cdot S_{u(t)}}{n_{u(t)}} + \frac{T - L_{u(t)}}{n_{u(t)}}}{T} .$$

Finally, in the MST scenario we have

$$e_u^{MST} = \frac{rx \cdot R_u + f(r_{u(t)}) \cdot S_u + T - L_u}{T} ,$$

where $r_{u(t)}$ denotes the transmitting range of node u computed at time t. Note that in the MST scenario the node load does not depend on time (actually, it is the same for all the nodes).

Observe that there is a clear trade off between the "quality" of the communication graph generated (low values of $\bar{T}$ are desirable) and the message overhead generated by the energy saving protocol (high values of $\bar{T}$ are desirable). An in depth investigation of this trade off, which we believe is very interesting, is beyond the scope of this paper, and it is matter of ongoing research. In our experiments, we have empirically set $\bar{T}$ to a value that provides a good balance between graph quality and communication overhead (see below for details).

An important aspect of the simulation of RWP mobile networks that has often been neglected is the choice of values for the mobility parameters. If these values (mainly, node velocity and pause time) are not chosen carefully, wrong conclusions about the network behavior in presence of mobility can be drawn. For instance, the conclusions that can be drawn when the nodes perform a small number of movements (say, around ten) may differ significantly from what can be construed when a large number of movements takes place. In fact, the initial node distribution (which is usually uniform) is different from the asymptotic spatial distribution generated by the RWP model, which tends to concentrate the nodes in the center of the deployment region.

In order to avoid such an undesirable effect, in our experiments we have set the parameters in such

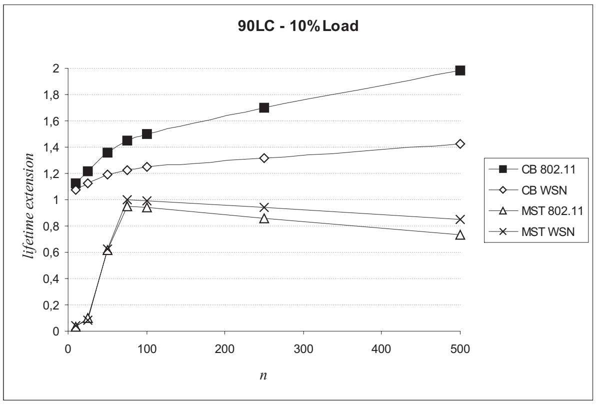

Figure 7: Lifetime extension for the CB and MST approach in mobile networks, for increasing values of n. The lifetime extension is expressed as a multiple of the lifetime in the NES scenario. The lifetime is defined as 90LC.

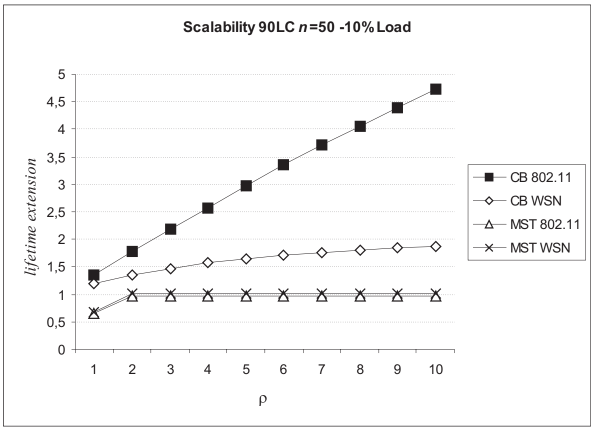

Figure 8: Lifetime extension for increasing values of the node density ρ. The lifetime extension is expressed as a multiple of the lifetime in the NES scenario. The lifetime is defined as 90LC.

a way so that nodes perform about one hundred movements (on average) during the observation period. In particular, parameters have been set as follows: $v_{min} = v_{max} = v = 0.01$, $t_{pause} = 0$, and $E_{init} = 4000$. The value of the velocity chosen resembles the high mobility scenarios reported in [9, 37]. As observed above, setting t_{pause} to zero corresponds to the maximum possible intensity of the border effect, and it is the most extreme case of node mobility.

6.2 Lifetime with minimum density

In the first set of experiments, we have evaluated the performance of CB and MST under the hypothesis that the node density is the minimum required to obtain connectivity w.h.p. We have considered the 1D and 90LC definitions of network lifetime, and set the value of T in such a way that the average load in the NES/CB scenario is 10%. As in case of stationary networks, we have considered both the 802.11 and the WSN energy models. The results of our simulations for the 90LC definition of lifetime, averaged over 100 experiments, are reported in Figure 7. Similar results have been obtained for the 1D notion of lifetime, which are not reported for lack of space.

The results show that CB provides significant lifetime extensions with respect to NES, especially in the 802.11 energy model. Furthermore, the extension increases with n. In the most favorable scenario ($n = 500$, 802.11 energy model), CB lifetime is 1.982 higher than in the NES scenario.

Contrary to CB, MST has a detrimental effect on network lifetime, in all the simulated scenarios. This fact merits some discussion. The choice of the period $\bar{T}$ used to recompute the nodes' transmitting ranges is particularly critical in the MST scenario. This is due to the fact that the MST is a very sparse graph, and relatively short movements are in general sufficient to cause disconnection. Thus, very small values of $\bar{T}$ would in principle be needed, making the implementation of MST-based topology control in mobile networks infeasible. To mitigate the poor connectivity of the MST in presence of mobility while keeping $\bar{T}$ at a reasonable value, we have increased the nodes' transmitting range by a constant term ϵ, which depends on the mobility parameters. There is a clear connectivity/energy consumption tradeoff in the choice of ϵ. In our simulation we have set ϵ to 0.03. This value of ϵ provides good connectivity, but reduces the average node lifetime, which is shorter than in the NES scenario. Note that the value of ϵ should in principle depend on n also; in particular, it should be larger for smaller values of n. This is the reason of the poor MST performance when $n \leq 50$.

Overall, the results of this set of experiments have shown that mobility has a positive effect on the performance of CB energy conservation. To make this point clearer, let us consider a network composed by $n = 100$ nodes, and assume a minimum density scenario. If the network is stationary, we must set r to 0.23530 and, assuming $E_{init} = 4000$ and the 1D definition of lifetime, we have a network lifetime with CB energy conservation of 3800 time units using the 802.11 energy model. If the network is mobile, we must set the nodes' transmitting range to $r_m = 0.2613$. Thus, the nodes consume more energy to transmit messages. Nevertheless, we have a network lifetime of 5770 time units, i.e., an increment of a factor 1.52 over the stationary case. This means that the positive "node shuffling" effect caused by node mobility outweighs the negative effect of the increased transmit power.

6.3 Lifetime for increasing density

In the second set of experiments we have investigated the scalability of the CB and MST performance as a function of node density. As in case of stationary networks, we started from the minimum density scenario with $n = 50$ and increased node density by distributing ρn nodes, with ρ in the range 2–10. Again, as in Section 6.2, we have considered an average load of 10%, and evaluated network lifetime with respect to the 1D and to the 90LC definition. The results of our simulations for the 90LC definition of lifetime, averaged over 100 experiments, are reported in Figure 8 (the results obtained with the 1D definition are very similar). The CB performance scales very well with ρ, especially in the 802.11 energy model. In this scenario, the network lifetime is extended by a factor of 4.72, when $\rho = 10$. Contrary to the case of CB energy conservation, the performance of MST-based topology control does not scale with node density, in any of the simulated scenarios.

7 Discussion and future work

Our study has yielded a number of interesting insights into the issue of network lifetime and the studied approaches to energy conservation. First, we have seen very little effect of the chosen lifetime definition on the results. Thus, whether we use time to first node death, time to disconnection, or time until the largest connected component drops below 90% of the nodes, the *relative* network lifetimes without energy conservation, with the cell-based cooperative approach, and with MST topology control remain approximately the same. Thus, even a simple lifetime definition such as time to first death seems to suffice when comparing the relative benefits of approaches. Another interesting finding is that, for reasons discussed in the paper, both energy conservation approaches can sometimes perform better at high loads, relative to a network without energy conservation.

In comparing the cell-based approach against MST topology control, we can summarize the results as follows. When node density is near the minimum necessary for connectedness, nodes are stationary, and the number of nodes is large, MST topology control performs better. The cell-based cooperative approach has a clear performance advantage over MST topology control when either the node density is quite high or nodes are mobile. In stationary networks with low load and a small number of nodes, neither approach significantly extends lifetime.

In comparing the analysis of cell-based approaches performed herein with previous work, particularly [5], we note that this paper includes a more realistic traffic model and also considers mobility. In [5], traffic was assumed to be the same in every cell and only stationary networks were considered.

In general, topology control increases network capacity because of reduced contention. This fact has not been considered in this paper, where contention is non-existent due to the perfect scheduling assumption. In other words, achieving a perfect scheduling in CB, especially with moderate load, could be very difficult. Refining our analyses to take collisions into account is the subject of future work. Other future areas of study include considering the effects of different values of mobility parameters and comparing against other topology control protocols, which produce denser graphs than MST but can perhaps balance load better.

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